

# Euclidean Invariant Computation of Salient Closed Contours in Images

by

**John Zweck<sup>1</sup> and Lance Williams<sup>2</sup>**

<sup>1</sup> Mathematics and Statistics, University of Maryland Baltimore County

<sup>2</sup> Computer Science, University of New Mexico

zweck@umbc.edu

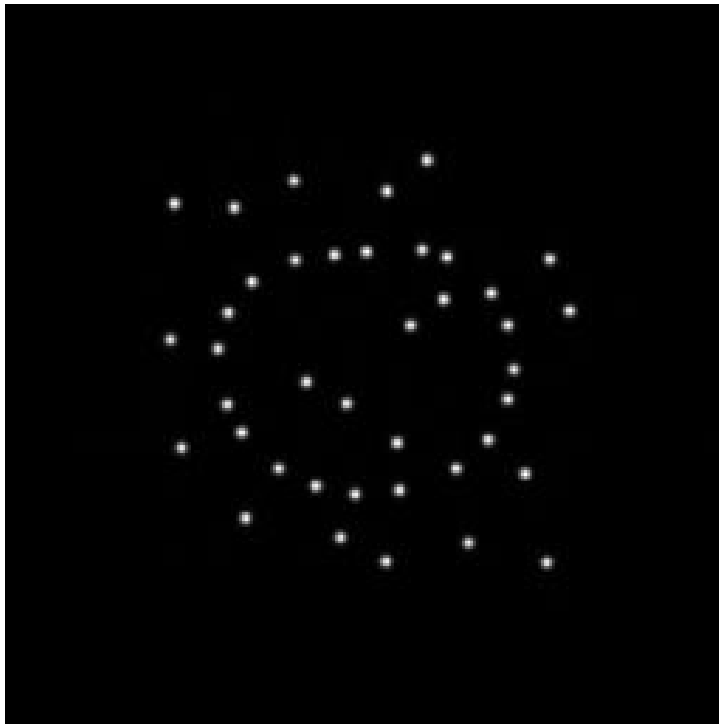
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# The Contour Completion and Saliency Problem

Compute the most salient closed curve in an image consisting of spots

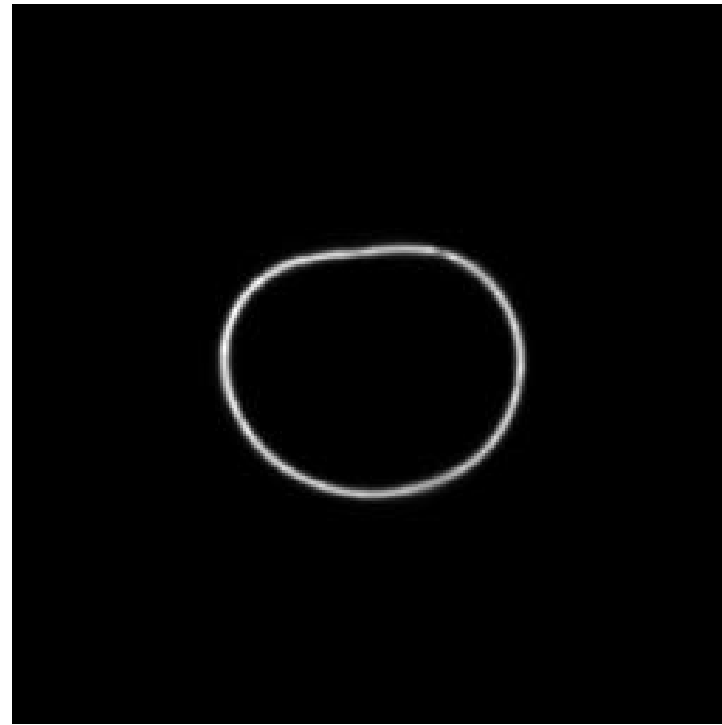
Input Spot Image

$$b : \mathbf{R}^2 \rightarrow \mathbf{R}$$



Stochastic completion field

$$c : \mathbf{R}^2 \times S^1 \rightarrow \mathbf{R}$$



$c(\vec{x}, \theta) =$  Probability a closed curve thru spots goes thru  $(\vec{x}, \theta)$

# Properties of computation

All functions are represented as  $f = \sum_{n=1}^N c_n \Psi_n$

The computation:

- Acts on the coefficients  $c_n$
- Is implemented in a finite discrete neural network
- Is based on a prior distribution of closed boundary contours
- Is Euclidean invariant in the continuum

# Prior probability distribution of boundary contours

- Boundary contours are characterized by a random walk on  $\mathbf{R}^2 \times S^1$ 
  - Particles move at constant speed in  $\mathbf{R}^2$  in direction  $\theta$
  - Direction  $\theta$  undergoes a Brownian motion on  $S^1$
- $P(\vec{x}, \theta; t)$  = Probability that a particle is at  $(\vec{x}, \theta)$  at time  $t$
- Fokker-Planck equation [Mumford, 1994]:

$$\frac{\partial P}{\partial t} = -\cos \theta \frac{\partial P}{\partial x} - \sin \theta \frac{\partial P}{\partial y} + \frac{\sigma^2}{2} \frac{\partial^2 P}{\partial \theta^2} - \frac{1}{\tau} P,$$

- Probability particle goes from  $(\vec{x}, \theta)$  to  $(\vec{y}, \phi)$ :

$$P((\vec{y}, \phi) \leftarrow (\vec{x}, \theta)) = \int_0^\infty P(\vec{y}, \phi; t) dt, \quad P(\vec{y}, \phi; 0) = \delta_{(\vec{x}, \theta)}(\vec{y}, \phi)$$

# Constraining the prior by a spot image

- Model input as finite collection of edges  $i$ :

$$b_i(\vec{x}, \theta) = \text{Prob}(\text{Edge } i \text{ is located at } (\vec{x}, \theta))$$

- Initially, no preferred orientations:  $b_i(\vec{x}, \theta) = b_i(\vec{x})$
- Assume edges are distinguishable:  $b_i(\vec{x}) b_j(\vec{x}) = 0$
- $b(\vec{x}) = \sum_i b_i(\vec{x}) = \text{Intensity of spot image}$

Markov process with states  $i$  and transition probabilities  $P(j \leftarrow i)$ :

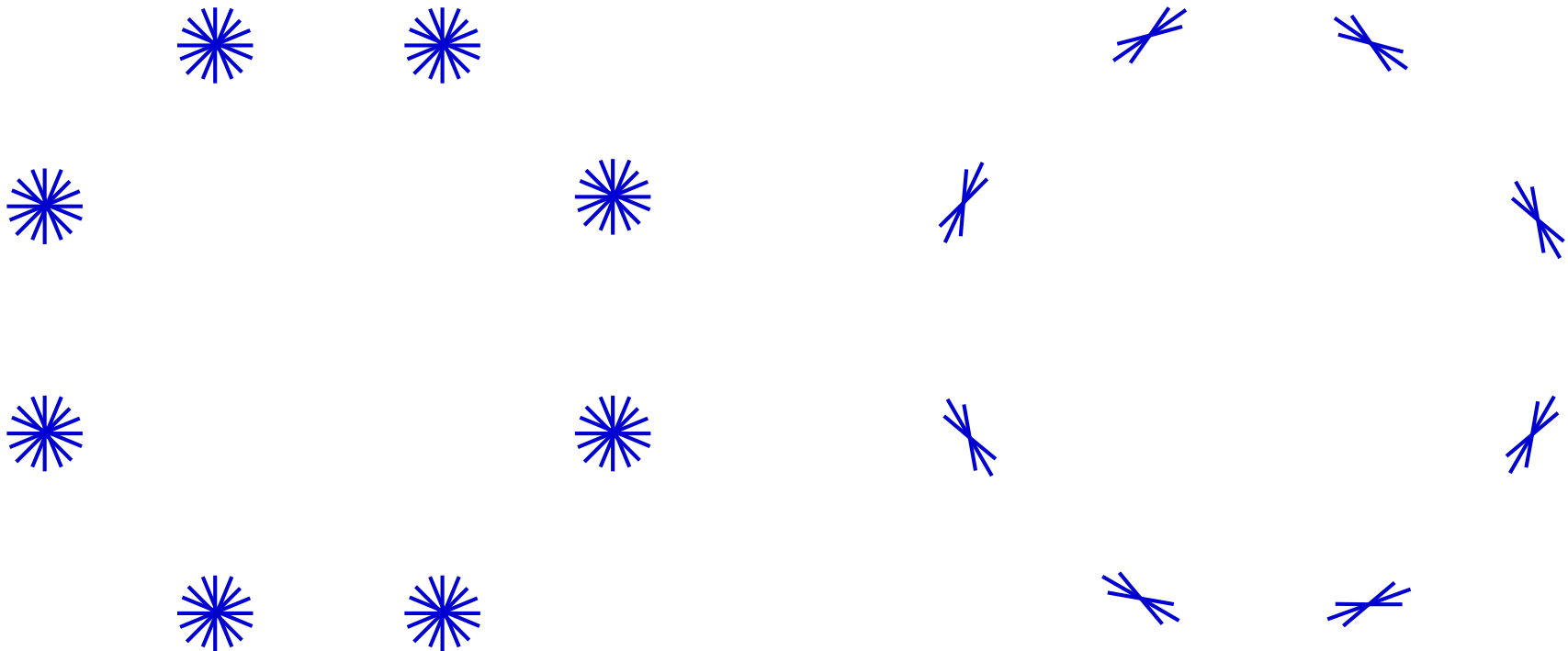
$$P(j \leftarrow i) = \iint b_j(y) P(y \leftarrow x) b_i(x) dx dy, \quad x = (\vec{x}, \theta)$$

# The eigensource and eigensink fields

- Let  $Q$  be the integral linear operator on  $L^2(\mathbf{R}^2 \times S^1)$  with kernel

$$Q(y, x) = b^{1/2}(y) P(y \leftarrow x) b^{1/2}(x)$$

- Let  $s$  and  $\bar{s}$  be eigenfunctions:  $Qs = \lambda_{\max}s$ ,  $\bar{s}Q = \lambda_{\max}\bar{s}$



# The stochastic completion field

- $c(\vec{x}, \theta)$  = Probability a particle starting at  $(\vec{x}, \theta)$  returns to  $(\vec{x}, \theta)$  after passing through a subset of the edges  $i$
- [Williams and Thornber, 2001] By Perron–Frobenius Theorem:

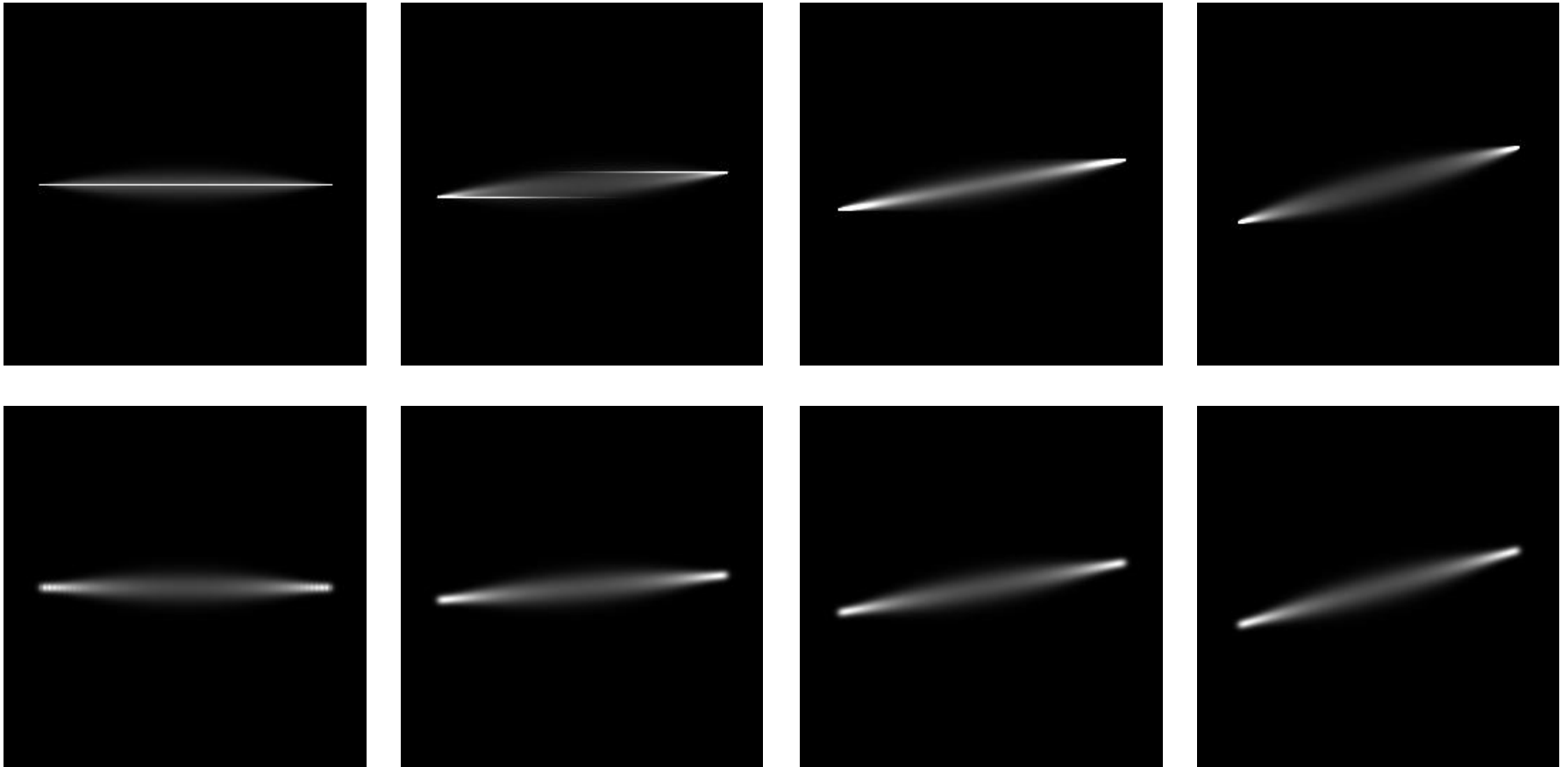
$$c(\vec{x}, \theta) = \frac{p(\vec{x}, \theta) \bar{p}(\vec{x}, \theta)}{\lambda_{\max} \int s(\vec{y}, \phi) \bar{s}(\vec{y}, \phi) d\vec{y} d\phi}$$

where the source and sink fields are

$$p = P b^{1/2} s \quad \text{and} \quad \bar{p} = \bar{s} b^{1/2} P, \quad \text{with } P(y, x) = P(y \leftarrow x)$$

**We want a  
biologically-plausible Euclidean-invariant computation of  $c$**

# Two Point Completion Fields



**Standard finite difference scheme in Dirac basis  
is *not* Euclidean invariant**



# Shiftable-twistable bases

- Shift-twist transformation on  $\mathbf{R}^2 \times S^1$ :

$$T_{\vec{x}_0, \theta_0}(\vec{x}, \theta) = (R_{\theta_0}(\vec{x} - \vec{x}_0), \theta - \theta_0)$$

- A computation  $C$  on  $\mathbf{R}^2 \times S^1$  is shift-twist invariant if:

$$\begin{array}{ccc} b & \xrightarrow{C} & c \\ T_{\vec{x}_0, \theta_0} \downarrow & & \downarrow T_{\vec{x}_0, \theta_0} \\ T_{\vec{x}_0, \theta_0} b & \xrightarrow{C} & T_{\vec{x}_0, \theta_0} c \end{array}$$

- A finite set  $\mathfrak{F}$  of functions on  $\mathbf{R}^2 \times S^1$  forms a shiftable-twistable basis if, for all  $(\vec{x}_0, \theta_0) \in \mathbf{R}^2 \times S^1$ ,

$$T_{\vec{x}_0, \theta_0}(\text{Span } \mathfrak{F}) \subset \text{Span } \mathfrak{F}$$

# The Gaussian-Fourier basis

- A periodic function  $\Psi : [0, X]^2 \times S^1$  is **shiftable-twistable** if

$$T_{\vec{x}_0, \theta_0} \Psi = \sum_{\vec{k}, m} b_{\vec{k}, m}(\vec{x}_0, \theta_0) T_{\vec{k}\Delta, m\Delta_\theta} \Psi$$

- Bandlimited functions are shiftable-twistable [Simoncelli *et al.*, 1992]
- The Gaussian-Fourier shiftable-twistable function:

$$G_\omega(\vec{x}, \theta) = \exp(-\|\vec{x}\|^2/2\nu^2) \exp(i\omega\theta)$$

- The Gaussian-Fourier shiftable-twistable basis:

$$\Psi_{\vec{k}, \omega} := T_{\vec{k}\Delta, 0} G_\omega$$

# Euclidean invariant computation of completion fields

- Computation acts on coefficient vectors  $\mathbf{s}$  of functions  $s$ :

$$s = \sum \mathbf{s}_{\vec{k},\omega} \Psi_{\vec{k},\omega}$$

- Represent action of  $Q = B^{\frac{1}{2}} P B^{\frac{1}{2}}$  on coefficient vector  $\mathbf{s}$  as

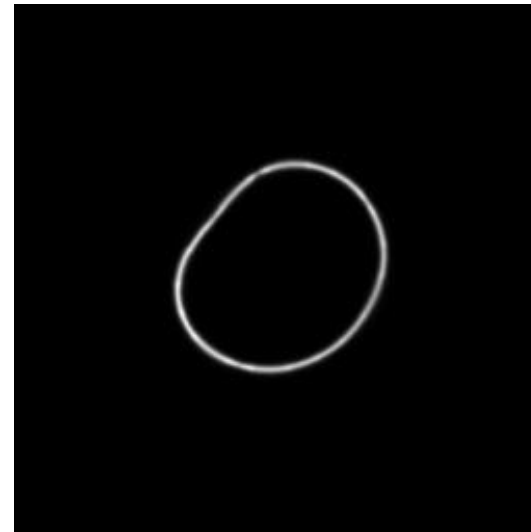
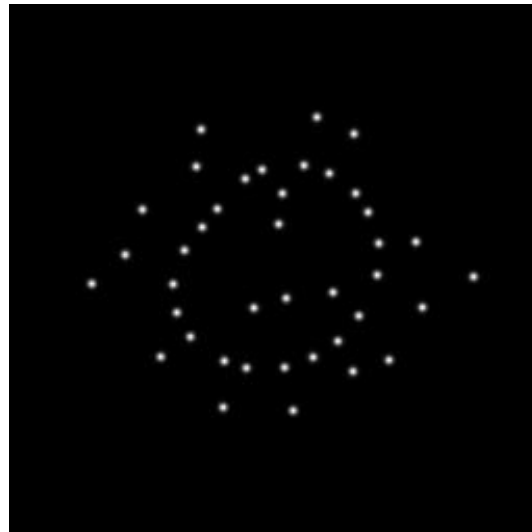
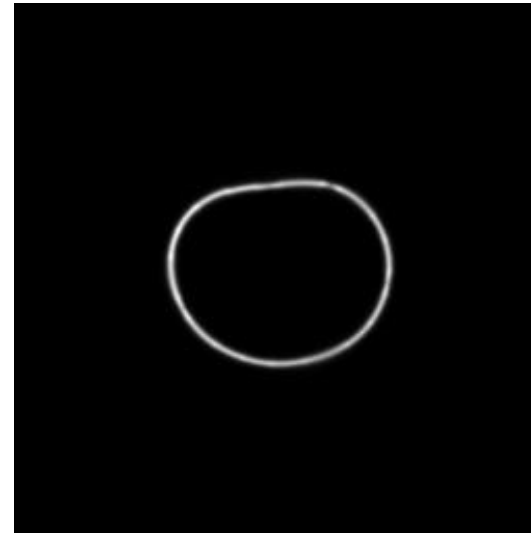
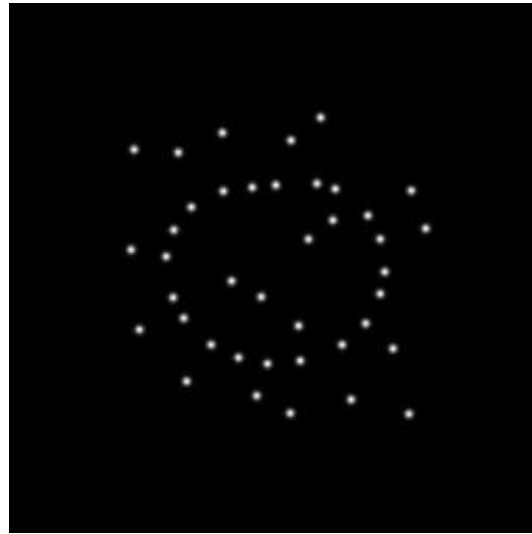
$$(\mathbf{Q}\mathbf{s})_{\vec{\ell},\eta} = \sum_{\vec{k},\omega} \mathbf{Q}_{\vec{\ell},\eta;\vec{k},\omega} \mathbf{s}_{\vec{k},\omega}$$

- Power method:  $\mathbf{s} = \lim_{m \rightarrow \infty} \mathbf{s}^{(m)}$  where  $\mathbf{s}^{(m+1)} = \mathbf{Q}\mathbf{s}^{(m)} / \|\mathbf{s}^{(m)}\|$
- Compute  $\mathbf{c}$  from  $\mathbf{s}$  and synthesize the completion field,  $c$

# Demonstration of Euclidean Invariance

$$b(\vec{x})$$

$$\int c(\vec{x}, \theta) d\theta$$



# Biological Motivation

Receptive fields in

- Lateral geniculate nucleus are *not* orientation sensitive (spot image)
- Primary visual cortex (V1) are orientation selective (source field)
- Secondary visual cortex complete contours (completion field)

Our computation suggests

Orientation selectivity in V1 is an emergent property of the higher-level computation of salient closed contours

# Conclusions

First discrete neural network that computes salient closed contours in images such that

- Input is isotropic, consisting of spots not edges
- Network computes a well-defined function of input
- Based on a distribution of closed contours
- Computation is Euclidean invariant in the continuum

# References

- L.R. Williams and J. Zweck, “A rotation and translation invariant discrete saliency network”, *Biological Cybernetics*, **88**, (1), pp. 2-10, 2003.
- J. Zweck and L.R. Williams, “Euclidean group invariant computation of stochastic completion fields using shiftable-twistable functions”, *Journal of Mathematical Imaging and Vision*, (to appear), 2003.